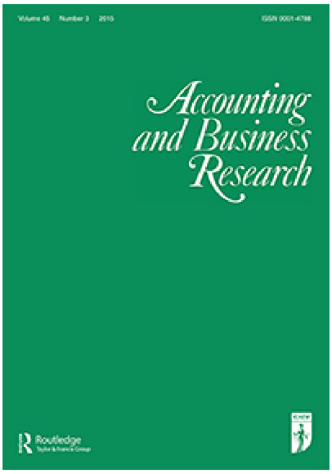

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Analysts' earnings forecasts: coexistence and dynamics of overconfidence and strategic incentives

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Analysts' earnings forecasts: coexistence and dynamics of overconfidence and strategic incentives

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This paper formulates a two-stage model to capture the decision process of financial analysts when issuing earnings forecasts. Our model extends the model of Chen and Jiang [(2005). Analysts' weighting of private and public information. *Review of Financial Studies*, 19 (1), 319–355], by allowing for a distortion of forecasts independent of whether an analyst has private information. Using quarterly earnings forecasts, we provide empirical evidence on the coexistence of overconfidence and strategic incentives. Financial analysts overweight their private information and at the same time strategically inflate their forecast.

Keywords: financial analysts; earnings forecasts; overconfidence; conflicts of interest
JEL classifications: G14; G17; G24

1. Introduction

Financial analysts are an important source of information to the stock market in the valuation of firms (Schipper 1991). They assimilate and process publicly available information, acquire private information and disseminate new information by issuing earnings forecasts and recommendations. It is, however, well documented that financial analysts' earnings forecasts systematically deviate from rationality (De Bondt and Thaler 1990, Abarbanell 1991, Brown 1997, Easterwood and Nutt 1999). Different explanations are put forward to explain these forecast inefficiencies. Broadly speaking, the systematic deviations from rationality in the decision-making process can be assigned to either a behavioral bias or a strategic bias (Friesen and Weller 2006).

Even though the literature analyzing financial analysts is quite elaborate, Ramnath et al. (2008) conclude that much of the decision process remains hidden in a black box. Studies often focus on either the behavioral bias (see e.g. Barber and Odean 2001, Hilary and Menzly 2006) or the strategic bias (see e.g. Dugar and Nathan 1995, Ljungqvist et al. 2007). When

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both biases are jointly taken into account, as in Chen and Jiang (2005), they are formulated as mutually exclusive hypotheses. In this paper, we therefore build upon this last model and extend it to incorporate distortions at two different stages, instead of a single distortion. Such a model allows to jointly determine a behavioral bias and a strategic bias and is therefore more flexible. In the first stage, analysts perform a fundamental analysis in which they combine public and private information to form their initial forecast. During this first stage, analysts can introduce a bias by over- or underweighting the information they have. In the second stage, a financial analyst can introduce an additional distortion by inflating or deflating his initial Bayesian forecast.

By introducing a two-stage model to explain analysts' decision process, we contribute to the literature in multiple ways. First, our model is more flexible. We not only introduce two different mechanisms by which analysts can distort their forecasts, but we also allow the analyst to distort his forecast, even in the case where he has no private information that he can over- or underweight. Second, by introducing two separate distortions, our model has the potential to separately capture the presence of a behavioral bias as well as a strategic bias. Therefore, a key feature of our model is that both biases, behavioral and strategic, can coexist and that we are able to identify the behavioral and strategic bias separately. This is in contrast to existing analytical models where these biases are typically modeled as mutually exclusive.

To test whether our model with two separate mechanisms of bias is empirically relevant, we estimate it on a large sample of quarterly earnings forecasts. In addition, we consider different settings that allow us to further analyze the two distortions in an attempt to define them as a behavioral or a strategic bias. We document the existence of two separate mechanisms of distortion. Our empirical results indicate that financial analysts overweight the precision of their private information and additionally inflate their forecast. Furthermore, we find that the first-stage bias resembles a behavioral bias, while the second-stage distortion appears to be strategic in nature. In particular, when estimating our model separately on a sample of male versus female analysts, we find that the first-stage distortion is significantly higher for male analysts than for female analysts. The second-stage distortion is similar for both. While differences among men and women should disappear among sophisticated individuals (see e.g. Croson and Gneezy 2009), Adams and Funk (2012) show that differences can still exist for a number of reasons, including gender discrimination in the access to the position. Interesting evidence is also given by Can Inci et al. (2014) who show that gender differences exist among senior executives due to differences in access to inside information. To further substantiate this finding, we show that the second-stage bias does conform to a strategic bias. In particular, the new analyst regulation enforced in 2002 to increase the objectivity of financial analysts, and thus targeted at the strategic bias, only impacts the second-stage distortion, and not the first-stage distortion. This suggests that this second-stage bias is driven by strategic considerations. Finally, a similar conclusion follows from the analysis of first forecasts versus last revisions. In line with the existing literature on the walk down from optimistic to more pessimistic forecasts within the same quarter (see e.g. Richardson et al. 2004), we also observe a walk down in the second-stage distortion. Again this leads us to conclude that this second distortion is strategic in nature.

The remainder of this paper is organized as follows. Section 2 discusses the two-stage decision model. Section 3 explains the empirical methodology and Section 4 presents the empirical results. Section 5 contains a robustness check, and finally Section 6 concludes.

2. The two-stage model

In this section, we introduce a two-stage model that represents the decision process of financial analysts. We build upon the model of Chen and Jiang (2005), but extend it to allow for a more generic decision process. The first stage of our model is identical to the Chen and Jiang (2005) model. Financial analysts perform an analysis in which they combine public and private information into an earnings forecast. The assimilation of public and private signals is modeled as a Bayesian expectation formation, which is a common approach in the earnings forecast literature (e.g. Chen and Jiang 2005, Martinez 2011). Following Gervais and Odean (2001) and Chen and Jiang (2005), a is defined as the announced earnings of a firm. These announced earnings follow a diffuse zero-mean normal distribution; c is defined as a statistic for all public information about a:

$$c = a + \varepsilon_c \quad \text{with } \varepsilon_c \sim N\left(0, \frac{1}{p_c}\right). \tag{1}$$

In this set-up, p_c is the precision of the public signal. We further assume that x is the analyst's private information about announced earnings a:

$$x = a + \varepsilon_x \quad \text{with } \varepsilon_x \sim N\left(0, \frac{1}{p_x}\right), \tag{2}$$

where p_x is the precision of the analyst's private signal and ε_x is independent from ε_c. Using Bayes' rule we define the analyst's best forecast of actual earnings conditional on his private information (x) and his public information (c) as

$$E(a|x, c) = hx + (1 - h)c, \tag{3}$$

where $h \cong p_x/(p_x + p_c) \in [0, 1]$ is the precision of the analyst's private signal relative to the public information. Of course, when an analyst interprets and weights publicly available information and private information, he may be influenced by a bias. This could lead him to deviate from the rational weighting scheme as summarized in h, and instead induce him to use his personal scheme k to obtain his Bayesian earnings forecast f_b:

$$f_b = kx + (1 - k)c, \tag{4}$$

where $k \in [0, 1]$ is the weight the analyst puts on his private signal. The more k differs from h, the more the analyst deviates from the optimal, rational forecast. An analyst who overweights private information is characterized by $k/h > 1$, while an analyst who underweights private information has $k/h < 1$.

While theoretically sound and attractive, the above specification only allows for a biased forecast in case there is a private signal x that is different from the public signal c. However, it could very well be that an analyst does not possess any private information and still issues a forecast that is different from the optimal consensus. Therefore, we want to allow for a more generic and flexible decision model, where distortion of the forecast is possible even if the analyst does not have a distinctive private signal. We therefore introduce a second stage, where an analyst can distort his initial Bayesian forecast f_b. This second-stage bias is modeled as a multiplicative distortion s of the initial Bayesian forecast f_b:

$$f = sf_b, \tag{5}$$

where f is the final earnings forecast as issued to the public and s the degree of second-stage distortion. An analyst who only strives for the most accurate forecast should have $s = 1$. A distortion factor $s \neq 1$ then corresponds to a strategic inflation/deflation of the Bayesian forecast, depending on the sign of this initial forecast. A distortion factor $s > 0$ implies that analysts do not change the sign of their initial forecast, while $s < 0$ implies that the sign of the initial Bayesian forecast is strategically reversed. For the empirical analysis in the current paper, where we restrict ourselves to positive final forecasts, we expect a distortion factor that is positive.[1] Intuitively, a distortion $s > 1$ then corresponds to strategic inflation, while a distortion factor $0 < s < 1$ points to deflation. A positive distortion factor is motivated by the evidence that forecast accuracy matters (see e.g. Gu and Wu 2003, Hilary and Hsu 2013), making it less likely that analysts reverse their initial Bayesian forecasts. This is reasonable for initial positive and initial large negative forecasts,[2] but it is possibly not valid for initial negative, but near-zero forecasts. For the latter, a reversal could be strategically interesting. However, the frequency of occurrence of such forecasts in our sample is most likely to be very low.

The identification of two separate distortions in our model is appealing. Indeed, as previous literature has shown analysts are prone to overconfidence as well as strategic incentives. Our model has the potential to capture both and to identify them separately if their dynamics are indeed different. The first-stage weighting scheme can either capture strategic incentives, behavioral bias, or both. The same holds for the second multiplicative distortion factor. Which distortions are present, and what its dynamics are, is ultimately an empirical question that we try to solve in this paper.

3. Estimation methodology

To obtain estimates of the two distortions, we need to rely on reduced form estimation. Using the above model set-up as defined in Equations (1)–(5), the expected forecast error can be defined as

$$E(\mathrm{FE}|x, c) = E(f - a|x, c) = s(kx + (1 - k)c) - (hx + (1 - h)c), \tag{6}$$

where $\mathrm{FE} = f - a$ is the forecast error. Rearranging and applying a first-order Taylor approximation to the biases around $k/h = 1$ and $s = 1$ allows for a separate identification of both biases:[3]

$$E(\mathrm{FE}|x, c) = \left(\frac{k}{h} - 1\right)(f - c) + (s - 1)f = \beta_1(f - c) + \beta_2 f, \tag{7}$$

where β_1 and β_2 reflect the first-stage and second-stage biases, respectively. If, in contrast to our hypothesis, only the first-stage bias distorts analysts' earnings forecasts, the model reduces to the moment condition $E[\mathrm{FE}] = \beta(f - c)$, as derived by Chen and Jiang (2005). If this is indeed the case, any additional term to this moment condition should not be empirically relevant, which implies $\beta_2 = 0$.

To test our model, the reduced form Equation (7) is estimated using the following regression model:

$$\mathrm{FE}_{ikt} = \alpha + \beta_1 \mathrm{Dev}_{ikt} + \beta_2 f_{ikt} + \delta_i X_{ikt} + \varepsilon_{ikt}, \tag{8}$$

with i being an analyst identifier (who issues the forecast), k a company identifier (on which a forecast is issued) and t a time identifier (to which quarter the forecast pertains). $\mathrm{FE}_{ikt} = f_{ikt} - a_{kt}$ is the forecast error made by analyst i in quarter t for company k, calculated as the difference between the forecasted f_{ikt} and actual a_{kt} earnings per share. $\mathrm{Dev}_{ikt} = f_{ikt} - c_{k\tau}$ is the deviation from the consensus and is determined as the difference between the analyst's forecast f_{ikt} and the consensus forecast $c_{k\tau}$. This consensus forecast proxies for available public information up to the point where an analyst issues his forecast. It is calculated as the mean of all estimates up to τ, excluding the estimate of the analyst i, who makes his estimate for quarter t (analogous to Zitzewitz 2001, Chen and Jiang 2005).[4] The forecast error, the deviation from consensus as well as the forecast are deflated by the share price. Finally, we include a set of control variables X_{ikt} that are known to be important determinants of the forecast error, while ε_{ikt} is the regression error term.

We want to stress that the consensus forecast $c_{k\tau}$ possibly contains industry-wide strategic biases of individual forecasts as modeled in Equations (4) and (5).[5] While it is likely that individual behavioral biases cancel out in the consensus, this may be less likely for individual strategic biases. In any case, the level of strategic distortion that an analyst decides upon is additional on potential strategic distortions present in the consensus. Our model thus captures the size of the strategic distortion, conditional on the average strategic distortion level that already exists.

4. Empirical results

4.1. *Data and descriptive statistics*

Quarterly earnings forecasts and stock price data are obtained from the Institutional Broker Estimate System (I/B/E/S) database, part of Thomson Financial. The earnings forecasts cover the period January 1996–December 2006. The database is restricted to highly covered US companies with a December fiscal year end. High coverage is ensured by demanding a minimum average coverage of three analysts, and by deleting firms with an average market capitalization below \$100 million, an average market price below \$5, or a market price below \$1. Furthermore, the data set is stripped from errors and potential companies in difficulties. As quarterly filings must be with the SEC within 45 days subsequent to the end of a quarter, observations of companies reporting later than this term are eliminated. In any given quarter, we keep the first forecast of analysts (similar to Francis and Philbrick 1993, Chen and Jiang 2005, Hilary and Menzly 2006). Choosing the first forecast ensures the largest set of observations drawn from the same distribution. Moreover, first forecasts are most timely and thus most valuable to investors. We furthermore drop negative earnings forecasts.[6] Such sample split is common in the earnings forecast literature, as it allows one to analyze the forecasts for which analysts have put in all of their effort. Indeed, Hayes (1998) concludes that the incentive to gather information is most intense for stocks that are anticipated to give strong performance. Furthermore, McNichols and O'Brien (1997) indicate that analysts drop stocks with unfavorable future prospects. Additionally, there are systematic differences in characteristics of forecasts for negative versus non-negative earnings firms (Dowen 1996).[7]

Finally, we include a set of control variables in our analysis. Following Clement (1999), size of the covered firm (Size_{kt}), general (TotExp_{it}) and firm-specific experience (FirmExp_{ikt}), two measures of task complexity (FirmCompl_{it} and IndCompl_{it}) and forecast age (Age_{ikt}) are controlled for. Our final sample consists of 322,123 earnings forecasts, issued by 6736 analysts on 2773 companies. A full description of all variables and their summary statistics and correlations can be found in Table A1 in Appendix 2.

4.2. *Main regression results*

The data set contains financial analysts' earnings forecasts for a particular stock at a certain point in time. This three-way panel possibly contains unobserved effects such as analyst, time, firm and industry effects. To control for these unobserved effects, Petersen (2008) argues that OLS with clustered standard errors (if necessary multi-way) is the best estimation method. Comparing clustered standard errors, in each dimension or multiple dimensions, with White (1980) standard errors, we conclude that standard errors clustered by business group are sufficient. Table A2 summarizes the estimation results of our two-stage model.[8] At the bottom of the table the weighting factor k/h and the strategic factor s are presented. They are calculated from the estimated parameters β_1 and β_2. Using the delta method, we know that the standard errors of k/h and s are the same as the standard errors of β_1 and β_2, respectively. For both factors, a two-sided t-test determines whether they are significantly different from 1.

Formulating estimates and standard errors on the two factors k/h and s allows us to determine their significance and compare both biases in magnitude. The weighting factor k/h is significantly larger than one at the 1% level. The estimate implies that financial analysts overweight the precision of their private information by about 2.5%. The inflation factor s is significantly larger than 1 at the 5% level. Financial analysts inflate their quarterly earnings forecast by roughly 3%. Thus, even in the absence of relevant private information, analysts distort their forecasts. This result is important, as it shows that an extension to the Chen and Jiang (2005) model is empirically relevant and allows us to better understand how analysts form their earnings forecasts.

4.3. *Identification of a behavioral bias and a strategic bias*

While the above full sample results indicate the coexistence of two separate distortions, further analysis can now shed light on the nature of these biases. Therefore, we re-estimate the model in different contexts or settings in an attempt to identify the behavioral from the strategic bias. In particular, we estimate our model separately for male and female analysts in an attempt to label one of the distortions as a behavioral overconfidence factor. We also estimate our model for a sample split at 2002, the year a new important regulatory framework for analysts was introduced. As this new regulation is targeted at banning conflicts of interest and thus at improving the quality of the analysts' research reports, we expect this change to have an effect on the strategic bias. Finally, to further confirm our model, we re-estimate the model on revised forecasts. This last analysis should pick up the observed walk down in earnings forecasts and should only have an impact on the strategic distortion.

Several academic studies show that men are more overconfident than women. Estes and Hosseini (1998) suggest that the most important factor for explaining investment decision confidence is the decision maker's gender. Deaux and Farris (1977) find that men claim more ability than do women and Prince (1993) reveals that men feel more competent than women with regard to financial matters. Of course, gender differences across the general population are not necessarily present among sophisticated individuals (see Croson and Gneezy 2009). However, Adams and Funk (2012) show that, even after controlling for observable characteristics, male and female directors do differ in their core values and attitudes toward risk. For example, female directors are less focused on power and more benevolent. In addition, Adams and Funk (2012) argue that gender effects may be driven by self-selection of women (see also Niederle and Vesterlund 2007). Further evidence on gender differences is also given by Can Inci et al. (2014) who argue that female executives seem to have a disadvantage in informal networks, and thus insider information, despite their equal formal status. Finally, Bosquet et al. (2014) show that male financial analysts are more likely to issue optimistic investment advice as compared to female analysts. Nevertheless, by estimating our two-stage model for male and female analysts we can analyze which distortion captures such behavioral difference between male and female analysts, and thus which distortion is likely to reflect behavioral factors.

To examine differences between male and female analysts, the gender of each analyst in our sample is determined. In the I/B/E/S Brokers Translation File every analyst is listed by its last name and first initial. This data set is merged with data from the corresponding annual edition of Nelson's Directory of Investment Research. This way the analyst's full name can be obtained on which basis gender is determined. We rely on a program that uses Google's database to analyze common patterns involving a first name.[9] The program determines whether the first name is more commonly used for a man or a woman. If there is uncertainty about the gender of an analyst, the history of that analyst is examined using the Internet to find out whether the analyst is male or female. For approximately 95% of the observations in the full data set it is possible to determine the gender of the analyst.[10] The other 5% of observations is removed from the data set. Finally, we remove analysts who cover an excessive amount of stocks (95th percentile), assuming that they are passing on information for an entire analyst team instead of one individual. The gender data set contains 293,386 observations of 5327 analysts on 2770 firms. Overall, 806 or 15% of the analysts in the data set are female.

To test our decision model on male and female analysts and to investigate the gender differences in overconfidence, we augment Equation (8) with dummy variables that indicate whether an analyst is male or female:

$$\begin{aligned}\mathrm{FE}_{ikt} = {} & \alpha_1 D_{\mathrm{m}} + \alpha_2 D_{\mathrm{f}} + \beta_{1,\mathrm{m}}(D_{\mathrm{m}} \times \mathrm{Dev}_{ikt}) + \beta_{1,\mathrm{f}}(D_{\mathrm{f}} \times \mathrm{Dev}_{ikt}) \\ & + \beta_{2,\mathrm{m}}(D_{\mathrm{m}} \times f_{ikt}) + \beta_{2,f}(D_{\mathrm{f}} \times f_{ikt}) + \delta_{i,\mathrm{m}}(D_{\mathrm{m}} \times X_{ikt}) \\ & + \delta_{i,f}(D_{\mathrm{f}} \times X_{ikt}) + \varepsilon_{ikt}.\end{aligned} \tag{9}$$

We use both a male dummy $D_{\mathrm{m}} = 1$ in case of a male analyst and $D_{\mathrm{m}} = 0$ otherwise, as well as a female dummy $D_{\mathrm{f}} = 1$ in case of a female analyst and $D_{\mathrm{f}} = 0$ otherwise. This facilitates the extraction of two bias parameters we are interested in, as well as the computation of the associated standard errors. Note that we can take into account a male and female dummy at the same time as the regression model above is formulated without a (general) constant term. Compared to a split sample approach, such dummy approach has the advantage of allowing for a covariance between the male and female observations.

Table A3 presents estimation results from Equation (8) presented separately for the male and female analysts. At the bottom of the table, the weighting factor k/h and the factor s for male and female analysts are presented. Compared to the rational Bayesian weight, male analysts overestimate their private information by 2.5%. This result is significant at the 99% confidence level. For female analysts the degree of overweighting is estimated at only 0.4%, and is not statistically significant from zero. The female weighting scheme is thus close to the rational scheme. More importantly, the difference between male and female analysts' weighting factor is significant at 95% (based on a one-sided test). While female analysts use rational Bayesian weights in processing public and private information, male analysts attach a weight to their personal information that is too high. This gender difference in the weighting of information leads us to conclude that the nature of this distortion is behavioral and can possibly be retraced to overconfidence. Moreover, this conclusion is further confirmed by analyzing the second-stage distortion. For this second-stage distortion, we find that male as well as female analysts positively inflate their Bayesian forecast, but that no significant gender difference can be observed. It is therefore most likely that this bias captures strategic incentives for which no gender-related prior exists.

While the above gender analysis suggests that the misweighting of private information corresponds to a behavioral bias, we perform an additional test on the inflation factor to document that the inflation factor indeed captures strategic incentives. To this end, we focus on the 2002 analyst regulation which was directed at eliminating analysts' conflicts of interest and thus strategic behavior by analysts.

After the dot-com bubble, it was clear that financial analysts were not free from conflicts of interest and that their recommendations and earnings forecasts were biased. On 10 May 2002, the SEC therefore approved the NYSE Rules 351 and 472 and the NASD Rule 2711,[11] collectively labeled 'SRO rules'.[12] These rules implement basic reforms to pursue the objectivity of financial analyst's research, and are directed specifically at the strategic behavior of financial analysts. If the second-stage inflation factor indeed corresponds to strategic incentives, we expect to observe a change in this factor. The behavioral first-stage factor should remain stationary.

We analyze the decision process for two separate time periods. The pre-2002 period runs from January 1996 until March 2002 and the post-2002 period runs from April 2002 until December 2006. Table A4 presents the estimation results of Equation (8), the weighting factor k/h and the strategic factor s for both samples. Testing the decision model in a time frame before and after the new regulation shows that behavioral overconfidence is unaffected by the introduction of new regulation (difference t-value of -0.69 is insignificant) but significantly different from zero in both sample periods. In line with our expectations, strategic distortion amounts to 5% before the new regulatory framework, and is estimated statistically significant at 99%. After the new SRO rules have been implemented this strategic bias drops to a low 2%, which is not significantly different from zero. Even though we cannot reject the hypothesis that the difference between both periods is zero, this decline in parameter value is in line with our expectations and supports the hypothesis that the inflation factor is strategic in nature.

In the final analysis, we study the earnings forecast walk down, characterized by optimistic forecasts in the beginning of a quarter to pessimistic forecasts near the end of the quarter. Such walk down has been linked to management pleasing, and thus can be attributed to strategic behavior of analysts. Constructing a sample of final forecasts within a quarter allows us to study whether our strategic component captures this walk down.

Richardson et al. (2004) document that analysts exhibit optimism at the start of the year, but then switch to pessimism in the final month prior to an earnings announcement. They suggest that management wants to sell stock on favorable terms after an earnings announcement. This is most likely with high market expectations after an earnings announcement but beatable targets before (see among others Bartov et al. 2002, Skinner and Sloan 2002). Therefore, strategic behavior in terms of management pleasing can be observed in initial optimistic forecasts, but subsequent pessimistic forecasts before the next earnings announcement.

Financial analysts issue an earnings forecast for a certain company in a certain quarter, but they can make a revision during the quarter. Pursuing an in-depth analysis of the decision process throughout the forecasting period requires us to compare the first forecasts (the existing sample) with the last revisions. The sample of last revisions contains the last forecasts within a quarter of analysts who have already issued a previous forecast during that quarter. The same adjustments are made to this sample of last revisions as to the existing sample of first forecasts. This results in a sample of 60,047 earnings revisions, issued by 4148 analysts on 747 companies.

Before reporting the regression results of the walk down of earnings forecasts, we descriptively compare the sample of first forecasts and last revisions over time. Figure A1 provides an overview of the quarterly average forecast error over time for the sample of first forecasts as well as for the sample of last revisions. This forecast error (FE), the difference between the forecast and the actual earnings, has an intuitive interpretation. A positive forecast error reflects optimistic behavior while a negative forecast error is defined as pessimism. The figure shows that, in the sample of first forecasts, average optimism turns into average pessimism after 2002. Analysts become less optimistic around 1999 and even pessimistic after 2002. This is in line with economic events such as the burst of the dot-com bubble and the introduction of new analyst regulation in 2002 as a reaction to a series of accounting scandals. The sample of last revisions shows that quarterly average forecast errors are almost consistently negative, implying that financial analysts are pessimistic when issuing their final revision. This is in line with findings of Markov and Tan (2006), who indicate that analysts have incentives to systematically underpredict earnings. Underpredicted earnings set beatable targets for firms' management, allowing for a positive earnings surprise. More importantly, the quarterly averages of the forecast error show that the last revision of financial analysts is always more negative than the first forecast. In summary, the figures already suggest a walk down at the consensus level and are therefore consistent with Richardson et al. (2004). Using our decision model we further analyze whether financial analysts consciously and strategically deflate their earnings revision as captured by the second-stage distortion.

Table A5 presents estimation results obtained from the reduced form estimation Equation (8) for the sample of last revisions. At the bottom of the table the weighting factor k/h and the strategic factor s are presented. We also report a two-sided t-test to determine whether they are significantly different from one. While in Table A2 the strategic factor s was significantly larger than one, the strategic factor s is significantly smaller than one in the sample of last revisions. Thus, while financial analysts strategically inflate their initial forecasts by roughly 3% (see Table A2 estimates), they strategically deflate their final revisions by approximately 5%, significant at the 1% level. In line with the existing literature, we thus document a significant walk down (difference t-value of -3.68, significant at the 1% level). At the same time, analysts still overweight their private information by about 3% when issuing their last revision (significant at the 1% level). This is similar to the degree of overconfidence observed in first forecasts (the difference t-value between the weighting factor from the last revisions and the first forecasts equals 0.30 and is insignificant). Therefore, in line with our expectations, only the strategic component alters when comparing first forecasts to last forecasts, while the weighting factor remains stable.

The ability of our model to capture different settings or contexts is a confirmation of its set-up. Not only is a two-stage decision model empirically relevant, but the two distortions are also different in nature. Where the first-stage misweighting is driven by behavioral conduct, a second-stage inflation or deflation occurs for strategic reasons.

5. Additional robustness test: negative earnings forecasts

Previous analyses are performed on positive earnings forecasts as Hayes (1998) argues that the incentive to gather information is most intense for stocks that are anticipated to give strong performance. Moreover McNichols and O'Brien (1997) indicate that analysts drop stocks with unfavorable future prospects. Table A6 summarizes the estimation results of our decision model as applied to negative earnings forecasts. Importantly, the interpretation of s is different for the subsample. An s smaller than one indicates strategic inflation (increasing the initial assessment), while an s larger than one indicates strategic deflation (lowering the initial assessment).

The estimation results show significant overconfidence at the 5% level. Financial analysts who do issue negative earnings forecasts overweight their private information by 6.8%. Our estimation results indicate that analysts make their initial assessment less negative, however the coefficient is not statistically significant. Our main results in Section 4 show how analysts consistently overweigh their private information and in addition inflate their assessment for strategic purposes. The results for the negative earnings forecasts are consistent with these main findings. Although not statistically significant, the strategic factor indicates inflation and again, analysts significantly overweigh their private information, even when it is negative.

6. Conclusion

Extensive research exists that aims to explain financial analyst behavior. However, the decision process of financial analysts is, to some extent, still a black box. In this paper we set up a two-stage model to further grasp the decision process of financial analysts. Our model builds on the model of Chen and Jiang (2005) by allowing for a distortion of forecasts whether or not analysts have private information. The inclusion of a second distortion also has the potential to separately define a behavioral bias from a strategic bias. When testing our model on a large data set of quarterly earnings forecasts, we find that our model is empirically relevant. In the first stage, financial analysts overweight private information by 2.5% and in the second stage they inflate their Bayesian assessment of earnings by 2.9%. Therefore, we conclude that our decision model with two distortions that impact forecasts differently coexist in financial analysts' earnings forecasts.

By estimating our model for different settings, we are able to label these distortions in terms of strategic and behavioral biases. In particular, we find that the gender stereotype that men are more overconfident than women is reflected in the first-stage misweighting of information, and not in the second-stage distortion. While male analysts overweight their private information, female analysts use a rational weighting scheme. Moreover, this gender difference is statistically significant. Analyzing the impact of the SRO ruling of 2002 further strengthens our model set-up. Indeed, this SRO ruling, intended to decrease conflicts of interest and thus strategic behavior, had an impact on the second-stage distortion, but not on the first-stage misweighting of information. Strategic behavior becomes insignificant after the introduction of the SRO ruling, while behavioral overconfidence is significant both before and after the regulatory action. Finally, we show that the well-documented walk down in earnings forecasts from optimistic in the beginning of the forecast horizon to pessimistic near the end, is picked up by our model by the second-stage bias, while leaving the first-stage bias unaffected. Again, this is in line with this second-stage inflation/deflation capturing strategic distortions.

Overall, our results indicate that our two-stage model functions well and captures main empirical facts about analysts' decision process. Through increased flexibility of our model as compared to the Chen and Jiang (2005) model, we are able to separately define a behavioral and a strategic bias that coexist and we show that it matters empirically.

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Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. We also estimate the model on the full sample of positive and negative forecasts, and results remain unchanged.
2. As analysts are reluctant to issue negative forecasts, stocks with such very negative future prospects are possibly dropped from coverage (see McNichols and O'Brien 1997).
3. A full derivation can be found in Appendix 1.
4. As a robustness check we also estimated a model that includes the deviation from the median consensus and we obtain similar results. These estimation results are available upon request.
5. We thank one of the referees for pointing this out.
6. Deleting negative forecasts implies a reduction in the data set of 11% from 362,040 to 322,123 forecasts. A sample of only positive forecasts still implies a symmetric loss function of forecast errors.
7. For completeness, Section 5 reports the estimation results of our model applied to the subsample of negative earnings forecasts. These findings are in line with our main conclusions. Also a full sample analysis, including both positive and negative forecasts was performed with similar outcomes.
8. Adding quarter dummies for a possible fixed time effect or adding industry dummies for a possible fixed industry effect leads to similar results. All conclusions remain the same.
9. http://www.gpeters.com/names/baby-names.php.

10. Also Green et al. (2009) and Kumar (2010) are able to match approximately 95% of the observations with gender.
11. National Association of Securities Dealers.
12. SRO stands for Self-Regulatory Organization Rulemaking. These new rules target research analyst conflicts of interest and aim to promote greater independence of research analysts. To this end, actual and potential conflicts of interest need to be disclosed to investors. See Securities Exchange Act Release No. 45908, 67 FR 34968 (16 May 2002). For a detailed explanation see http://www.sec.gov/rules/sro/34-48252.htm.

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Appendix 1. Deriving the regression equations

To derive to the estimation equation as summarized in Equation (8), we start from the expected forecast error:

$$\begin{aligned} E(FE|x,c) &= E(f-c|x,c) \\ &= s(kx+(1-k)c)-(hx+(1-h)c) \\ &= skx+(s-sk)c-hx-(1-h)c \\ &= \frac{h}{k}c-\frac{h}{sk}f+(f-c). \end{aligned}$$

Rearranging allows for a clear identification of both the stages of biases impacting an analyst's forecast and forecast error:

$$E(FE|x,c) = \left(1-\frac{h}{k}\right)(f-c)+\frac{h}{k}\left(\frac{s-1}{s}\right)f.$$

Applying a first-order Taylor approximation to both coefficients in the equation above around $k/h = 1$ and $s = 1$, the reduced form moment condition is transformed into

$$\begin{aligned} E(FE|x,c) &= \left(\frac{k}{h}-1\right)(f-c)+(s-1)f \\ &= \beta_1(f-c)+\beta_2 f. \end{aligned}$$

This allows for a clear separation of the two biases in β_1 and β_2, respectively.

Appendix 2. Tables

Table A1. Summary statistics.

Panel A of this table presents the descriptive statistics of the forecast error, the deviation from consensus, the earnings forecast (deflated) and the control variables used in Equation (9). Outliers are removed by deleting the top and bottom 0.1% for the variables forecast error, deviation and earnings forecast. The earnings forecast data are obtained from I/B/E/S. Panel B of this table shows the correlations.
FE is the difference between the earnings forecast and the actual, deflated by the share price. Dev is the difference between the earnings forecast and the consensus forecast, deflated by the share price. f is the analyst's earnings forecast, deflated by the share price. Age is the number of days between the issue of the analyst's earnings forecast and the reporting date of the actual earnings. Size is the logarithm of the market capitalization, calculated in the month prior to the forecast. FirmExp is the number of quarters an analyst has followed a certain stock. TotExp is the number of quarters the analyst is present in the data set. For both ability variables, data starting from 1992 are used to prevent all analysts from starting with the same experience in 1996. FirmCompl is the number of companies an analyst follows during a quarter. IndCompl is the number of sectors an analyst follows during a quarter. I/B/E/S identifies 11 sectors using a proprietary classification scheme for companies with similar business lines.

Panel A: Descriptive statistics.

	Mean	Std dev.	Min	Max
FE	3e−0.06	0.01	−0.25	0.68
Dev	0.01	0.01	−0.11	0.53
f	0.01	0.01	0.00	0.53
Age	73.87	26.13	1.00	143.00
Size	7.93	1.32	−5.32	12.34
FirmExp	11.46	10.36	1.00	59.00
TotExp	20.72	13.39	1.00	59.00
FirmCompl	9.22	5.89	1.00	67.00
IndCompl	1.71	0.94	1.00	9.00

Panel B: Correlations.

	FE	Dev	f	Age	Size	FirmExp	TotExp	FirmCompl	IndCompl
FE	1.00	0.05	0.04	0.02	−0.05	0.00	−0.01	−0.01	−0.01
Dev		1.00	0.41	0.34	−0.06	0.01	0.03	0.00	0.04
f			1.00	−0.02	0.03	0.08	0.06	0.11	−0.03
Age				1.00	−0.04	−0.01	0.03	−0.08	0.07
Size					1.00	0.21	0.09	0.12	−0.10
Firmexp						1.00	0.60	0.17	0.02
TotExp							1.00	0.21	0.12
FirmCompl								1.00	0.12
IndCompl									1.00

Table A2. Main estimation results.

This table presents coefficient estimates and t-values for the reduced form estimation equation (Equation 8). The data cover the period January 1996–December 2006 and only positive forecasts have been used, yielding a data set of 322,123 observations. A firm-fixed effects estimation is used with clustered standard errors by business group. These clustered standard errors are White (1980) standard errors adjusted to account for possible correlation within a cluster, i.e. business group. This table also reports the estimation results for the weighting factor k/h and the strategic factor s. For both factors the two-sided hypothesis test whether they are significantly different from 1 is performed. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	Coeff.	t-Value
Dev (β_1)	24.9e−03	4.17***
f (β_2)	29.3e−03	2.13**
Age	49.0e−07	3.05***
Size	−20.0e−05	−1.83*
FirmExp	−18.0e−07	−0.96
TotExp	8.0e−07	0.66
FirmCompl	−7.0e−07	−0.48
IndCompl	−7.0e−07	−0.08
k/h	1.025	4.17***
s	1.029	2.13**
Adj. R^2	0.47%	
Nobs	322,123	

Table A3. Estimation results for gender stereotype: a behavioral bias.

This table presents estimation results for the reduced form estimation Equation (8). The data cover the period January 1996–December 2006 and only positive forecasts have been used, yielding a data set of 322,123 observations. A firm-fixed effects estimation is used with clustered standard errors by business group. These clustered standard errors are White (1980) standard errors adjusted to account for possible correlation within a cluster, i.e. business group. At the bottom, this table presents the estimation results for the weighting factor k/h and the strategic factor s for the male and female analysts. For both factors the two-sided t-test whether they are significantly different from 1 is performed. For the gender difference with respect to the factors, a two-sided t-test is reported in the final column. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	Male analysts		Female analysts		
	Coeff.	t-Value	Coeff.	t-Value	
D	0.18e−03	4.98***	−0.11e−03	−0.87	
Dev (β_1)	24.98e−03	4.01***	3.85e−03	0.33	
f (β_2)	26.66e−03	1.89*	39.24e−03	2.14**	
Age	51.00e−07	3.15***	70.00e−07	3.57***	
Size	−18.59e−05	−1.70*	−19.11e−05	−1.73*	
FirmExp	−3.00e−07	−0.20	37.00e−07	0.72	
TotExp	−14.00e−07	−1.05	−9.00e−07	−0.30	
FirmCompl	−60.00e−07	−2.00**	−10.20e−06	−0.95	
IndCompl	−35.50e−06	−2.61***	76.40e−06	1.69*	
					Diff. t-value
k/h	1.03	4.01***	1.00	0.33	1.61*
s	1.03	1.89*	1.04	2.14**	−0.54
Adj. R^2	0.45%				
Nobs	293,386				

Table A4. Estimation results for the 2002 SRO regulation change: strategic distortion.

This table presents coefficient estimates and *t*-values for the reduced form estimation Equation (8) for the pre-2002 period and the post-2002 period. The data cover the period January 1996–December 2006 and only positive forecasts have been used, yielding a data set of 322,123 observations. The cutoff point is the second quarter of the year 2002. The pre-period runs from January 1996 until April 2002 and the post-period runs from April 2002 until December 2006. For all regressions, firm-fixed effects are used with clustered standard errors by business group. These clustered standard errors are White (1980) standard errors adjusted to account for possible correlation within a cluster, i.e. business group. At the bottom, this table presents the estimation results for the weighting factor *k*/*h* and the strategic factor *s*. For both factors the two-sided hypothesis test whether they are significantly different from 1 is performed. In the final column a difference *t*-value is reported on the difference between the weighting factor and the strategic factor pre- and post-2002. The earnings forecast data are obtained from I/B/E/S. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	Pre-2002		Post-2002		
	Coeff.	*t*-Value	Coeff.	*t*-Value	
Dev(β_1)	34.0e−03	3.18***	24.5e−03	2.90***	
$f(\beta_2)$	51.6e−03	2.73***	17.4e−03	0.74	
Age	80.0e−07	4.75***	26.0e−07	1.17	
Size	−26.0e−05	−1.93*	20.0e−05	1.05	
FirmExp	22.0e−07	0.73	21.0e−07	−1.39	
TotExp	−56.0e−07	2.28**	20.0e−08	0.19	
FirmCompl	−58.0e−07	−2.24**	−11.0e−07	−0.37	
IndCompl	−14.7e−06	−0.93	−31.0e−07	−0.23	
					Diff. *t*-value
k/*h*	1.03	3.18***	1.02	2.90***	−0.69
s	1.05	2.73***	1.02	0.74	−1.14
Adj. R^2	1.28%		0.26%		
Nobs	154,210		167,913		

Table A5. Empirical results for Forecast Walkdown: strategic distortion.

This table presents coefficient estimates and *t*-values for the reduced form estimation Equation (8) for the sample of last revisions. The data cover the period January 1996–December 2006 and only positive forecasts have been used. A firm-fixed effects estimation is used with clustered standard errors by business group. These clustered standard errors are White (1980) standard errors adjusted to account for possible correlation within a cluster, i.e. business group. At the bottom, this table presents the estimation results for the weighting factor *k*/*h* and the strategic factor *s*. For both factors the two-sided hypothesis test whether they are significantly different from 1 is performed. The earnings forecast data are obtained from I/B/E/S. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	Coeff.	*t*-Value
Dev (β_1)	27.5e−03	4.29***
f (β_2)	−47.5e−03	−3.02***
Age	−7.00e−07	−0.28
Size	20.00e−05	1.55
FirmExp	−27.00e−07	−1.70*
TotExp	−5.00e−07	−0.45
FirmCompl	−3.0e−07	−0.09
IndCompl	−72.0e−07	−0.36
k/*h*	1.028	4.29***
s	0.952	−3.02***
Adj. R^2	0.93%	
Nobs	60,047	

Table A6. Empirical results for negative earnings forecasts only.

This table presents coefficient estimates and t-values for the reduced form estimation Equation (8) for negative earnings forecasts. The data cover the period January 1996–December 2006. A firm-fixed effects estimation is used with clustered standard errors by industry. We use 11 industry groups to cluster the standard errors instead of 211 business groups. The sample size of the last revision sample is not sufficient to have enough observations for each of the 211 clusters. At the bottom, this table presents the estimation results for the weighting factor k/h and the strategic factor s. For both factors the two-sided hypothesis test whether they are significantly different from 1 is performed. The earnings forecast data are obtained from I/B/E/S. *,** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	Coeff.	t-Value
Dev (β_1)	67.6e−03	2.84**
f (β_2)	−20.9e−03	−0.40
Age	33.1e−06	3.19***
Size	−12.1e−04	−0.60
FirmExp	48.8e−06	1.37*
TotExp	−6.8e−06	−0.34
FirmCompl	−14.3e−06	−0.35
IndCompl	21.7e−05	−3.70***
k/h	1.07	2.84**
s	0.98	−0.40
Adj. R^2	0.60%	
Nobs	39,917	

Figure A1. Average FE of first forecast and last revision.
This figure shows the quarterly average FE for the sample of first forecasts and the sample of last revisions over time, deflated by the stock price. The time period covers January 1996 until December 2006.